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NEURAL NETWORK SUPPORT FOR INTROSCOPY OF INTERNAL STRUCTURE AND PROPERTIES OF THE BUILDING CONSTRUCTIONS

Abstract. Introscopy is a process of contactless, non-destructive analysis of the internal structure of an object or processes in it using X-ray radiation, optical, acoustic, ultrasonic, seismic, electromagnetic waves of various ranges, modulation and coding principles. Its implementation involves methods for obtaining shadow, tomographic, radar and other images of the object of study. The resulting image contains information about the object. Image analysis and decision-making about the object structure or its condition is carried out by an expert (operator). Obviously, the decision is made subjectively; its effectiveness depends on the qualification of the expert and can be significantly reduced because of the increasing number of errors and analysis time. In real conditions, the classification of the state of the object of study with a significant number of signs, with their unstable or uninformative degree of knowledge extraction, seems to be not a trivial task. To date, however, image recognition technologies based on artificial intelligence technologies have been developed and implemented that make it possible to synthesize neural network classifiers in vision systems that are invariant to the physical features of feature spaces of the studied object images. For introscopy technology, it has been prepared a neural network information-analytical, software and instrumental basis for solving the task of automating of the process of image visualization and its identification in the paradigm of designing and recognizing images in the space of shadow, tomographic, multi-view signs using statistical decision rules. The developed technology is represented in the form of an ensemble of neural network classifier models that implemented as independent software applications in the main code of an existing technical analysis package, for example, the neuro-emulator of StatSoft environment. The synthesis of classifier models according to the input data of images based on shadow and tomographic raster sweeps in a standard package of neuroemulators allows us to solve the problem with minimal cost and required quality indicators. Studies of the characteristic spaces of the introscopy process, the possibilities for the correct application of statistical decision rules, algorithms for the compulsory training of synthesized neural network models in the basis of existing technical data packages can improve the productivity of introscopy equipment by automating the analysis process, reducing the impact of subjective decisions, and reducing reaction times.

Keywords: analytical complex, introscopy, neural network, resilient backpropagation, real-time classifier.

Introduction

Introscopy is a process of contactless, non-destructive (non-invasive) analysis of the internal content, structure of an object or processes in it using X-ray, optical, acoustic, ultrasonic, seismic, electromagnetic waves of various ranges, modulation and coding principles [1].

Introscopy provides visual observation of the internal structure of objects and processes in optically non-transparent media, as well as in conditions of poor visibility due to natural or deliberate masking factors. Introscopy is carried out by means of visualization of the spatial distribution of penetrating radiation and fields in the frequency spectrum of the entire developed range of electromagnetic oscillations of electric fields, as well as the fluxes of elementary particles.

The scope of introscopy is quite wide [1, 2]. This is medical and technical diagnostics, analysis of macro-objects and processes occurring in them (observation of objects under water, in the thickness of rocks and glaciers, in clouds, fog, etc.). Each area of this technology application has its own characteristics associated with the visualization of the object of study, its recognition and analysis of the internal structure and properties, the choice of performance criteria with limited resources. Let us consider the possibilities of introscopy technology in relation to the field of

construction, for the tasks of analyzing the state of the internal structure and properties of construction objects (bridge supports, overpasses, building foundations, road pavement, waterproof and heat saving properties of coatings, etc.)

The basis of introscopy involves methods for obtaining shadow, tomographic, radar, and other images of the object of study using optical, acoustic, electromagnetic or X-ray radiation.

Information about the structure and properties of the object of study is contained in the resulting image (snapshot), which can be multi-angle, shadow and tomographic [3,4,5]. The existing analytical complexes (AC) are intended for introscopy of large-sized objects having significant size, weight, composition of construction materials. By mobility, ACs are classified into fixed, relocated, and mobile. An expert (operator of the introscope) performs image analysis and decision making depending on the structure and properties of the object of study. Obviously, the decision is made subjectively, based on knowledge, qualification, and experience. In the conditions of aging, normal wear and tear or violation of the technology of manufacturing components, the expert may have difficulties with accurate and rapid identification of the object state. It is reasonable to automate this process by transferring the functions of image analysis to a program that recognizes images of the internal structure and properties of the

objects of study, compares them with the appropriate conclusion, which improves performance, speed and reduces costs [6, 7].

The technical characteristics of existing joint stock companies provide the ability to visualize the internal structure of objects of study, their properties and ingredient composition, recognition of missing or non-conforming ingredients, their density, thermal conductivity, insulating properties, etc.

The equipment allows for a detailed, fragmentary view of individual zones of the object of study and its contents and magnification of the image several times. The time of introscopy of one large object is 15-30 minutes [1, 2].

The ultimate goal of introscopy is to establish the affiliation of the studied objects to certain groups, types, classes, to identify characteristic structural defects, signs of aging, loss of working properties, hidden defects, inconsistencies with technical conditions and state standards in controlled objects.

In the process of this action, the operator of the introscope analyzes a visual image of the internal contents of the objection the installation screen, and classifies the object of study according to the set of characteristic individual features [4, 5].

The most difficult and important is the knowledge of the set of characteristic features and their connection with the required characteristics of the objects of study. However, the proposed technology allows, on the one hand, to use the existing database [1, 2], on the other – to create this database on its own, forming a representative sample of examples in the process of production of building structure components.

In the course of AC operation, one of its most important problems was revealed – it is the excessive dependence of the analysis result on the human factor in the operation of the analysis system. The lack of appropriate data mining technologies that can support decision-making by the operator or, in general, assign this task to a computer program is emphasized as a disadvantage. At present, it is problematic for the fleet of operated ACs to fully automate the operational analysis of building structures. Secondly, the analysis time depending on the type of AC is 15-30 minutes or more, which significantly limits the throughput and leads to economic losses.

Thus, in the trend of total digitalization of economy, automation and robotization of production in the paradigm of the growing new technologies, there is a practical need for information and technical support for the state of existing ACs in order to increase their efficiency and competitiveness in the market for analytical analysis of building structures.

Analysis of the possibilities of AC information and analytical support

The well-known specialists in this field [1–5] were engaged in the development, theoretical substantiation, and introduction of the technology of introspecting objects: P.N. Afonin – theory and practice of using technical means of control; V.A. Soifer, U. Pratt –

computer and digital image processing; S.K. Ternovoy, E.N. Simonov – X-ray computed tomography; G.M. Agadzhanian, A.P. Krasnitsky – vision systems and others. As a result of their activity, the technologies of functioning of the existing IDC have been created.

However, scientists V.M. Glushkov, T. Kohonen, S. Khaikin, R. Hecht-Nielsen and others [7] developed, theoretically substantiated and implemented in practice technology of recognition, prediction, adaptation based on artificial intelligence technology. Their activities have brought into existence:

- fundamental principles of recognition and methods of applied theory of artificial intelligence in technical systems;
- approaches to the design and modeling of technical vision systems invariant to the physical features of the feature spaces of the studied images of objects and phenomena;
- methods and algorithms of multilevel differential diagnostics in various subject areas;
- algorithmic and software products for operational multivariate data analysis in the tasks of classification and forecast;
- complex qualimetry of basic processes of complex technical systems.

Thus, there is an information-analytical, software and instrumental basis for successfully solving the task of automating of the process of image visualization and its identification in the paradigm of designing and recognizing images in the space of shadow, tomographic, multi-view signs using statistical decision rules under given constraints.

Purpose of the study is increasing the productivity of technical means of introscopy based on neural network support for analyzing video images in order to automate the analysis process, reduce erroneous decisions, to reduce reaction time during decision making, and to minimize the potential damage. The developed technology will be represented in the form of an ensemble of neural network classifier models that implemented as independent software applications in the main code of an existing technical analysis package, for example, the neuro-emulator of Stat Soft environment.

Formulation of the problem

Formalization of the process of classifying the internal structure of the object of study is mapping the input vector of data to the result of the examination, and approximating the dependence “object – class”. Generally, the signs of behavior and the number of object classes are vector quantities. The analysis task is to convert the primary features of object images into an array of raster scan elements followed by fixation, digitization of the luminous intensity of compact objects and their identification based on the generated databases and synthesized patterns of image classification in the space of selected shadow, tomographic, multi-view informative features.

If we accept the implementation of the technology of forming the array of features presented in the sources

[1-4] and describe the corresponding classes of the studied images according to the method described in [5,6], then formally the research task can be represented as [7]:

$$\begin{aligned} &SupK_E(S, P, X, T_k); \\ &\mathfrak{R}u(\Delta T) \leq A_0; \quad , \quad (1) \\ &\mathfrak{R}u(\delta) \leq B_0, \end{aligned}$$

where $s \in S$, S is the set of the current state of the object;

$p \in P$, P is the set of the forecasts of the object state;

$x \in X$, X is the set of the input factors;

$T_k, k \in \{0, 1, 2, \dots\}$ are decision points;

K_E is a performance criterion;

$\Delta T, \delta$ are the time interval for making a decision and the current degree of the model adequacy, respectively;

$\mathfrak{R}u(\Delta T)$ is expected damage from delayed decision;

$\mathfrak{R}u(\delta)$ is expected damage from the degree of the model inadequacy;

A_0 is allowable damage from the decision at the border RT;

B_0 is allowable damage from errors on the control set.

The main task of the analysis is to assess the internal structure and properties of the object of study, therefore, we formally consider this process to the level of the decision rule. Let there be a list of objects in a certain subject area W , where

$$W = \{\omega_g\}, g \in \bar{I} = \{1, 2, \dots, I_m\}$$

and let their belonging to some classes be fixed $\Omega_p, \Omega_g = \{1, 2, \dots, J_i\}$.

The problem of classifying them to a particular class is solved with certain errors and time expenditures. If limitations were not taken into account, the whole set of features could be used regardless of their information capabilities. Otherwise, recognition algorithms should include temporary ($t < T_0$) and material ($s < S_0$) restrictions where T_0 and S_0 , respectively, are the allowable (disposable) time and material resources for the implementation of software and tools in the task of recognizing objects or their states. At the same time, the power of the decision rule M must not be lower than the specified one (M_0): ($M > M_0$). Then, you can group objects by analyzing and grouping their feature spaces.

Grouping of objects, taking into account the analysis of the compactness of their features, can be formally represented by a functional [7]:

$$G = F \left[r(\Omega_p); R(\Omega_p, \Omega_g); A(\omega, \{\omega_g\}) \right], \quad (2)$$

where $r(\Omega_p)$ is removing traits inside a class;

$R(\Omega_p, \Omega_g)$ is removing traits in different classes;

$A(\omega, \{\omega_g\})$ is an object allocation rule ω_g from the set ω – to the class $\Omega_k : \omega_g \in \Omega_k$ provided that

$$\begin{aligned} &A(\omega, \{\omega_g\}) = \max_i A(\omega, \{\omega_i\}), \\ &(M > M_0), (t < T_0), (s < S_0). \end{aligned}$$

In this case, the objects should be grouped in the format:

$$\mathfrak{R}_0(\omega_{pk}, \omega_{gl}) = \sum_{j=1}^N (x_{pk}^{(j)} - x_{gl}^{(j)}) -$$

metric of compactness of signs in classes p, g in the analysis of k, l – objects of j – type.

Thus, we have a formulated optimization problem of identifying the internal structure of the object of study, the implementation of which requires a software and instrumental justification and adequate models for obtaining practical results.

The basis of solving the problem is the principle of extracting knowledge through the implementation of model learning processes with modification of weighted synaptic coefficients and adapting the criterion of its productivity by selecting the optimal set of input features for information value and material costs over a set time [6, 7].

Analysis of existing software and hardware has led to the conclusion about the feasibility of using technical data analysis packages as basic tools, which implement training procedures, data exploration, dimension reduction algorithms and the fundamental possibility of quantifying the information value of the input set of factors [7]:

$$|Y(t)| = F|X(t)|,$$

where $|Y(t)|$ is an object state class number;

$|X(t)|$ is an input feature vector;

F is the functional of converting an array of attributes into a class number, as a set of procedures for describing classes in the language of their attributes, preprocessing data, reducing the dimension of the input vector, standardizing inputs, synthesizing models and learning them, interpreting results.

It is proposed to use the trained artificial neural network with the reverse spread of the error as a tool for automatic recognition of the state as the basis of classification [6].

Solving a problem of the form (2) with constraints from the general problem (1) requires satisfying the decision condition in real time (RT). This is possible when taking into account the following features:

- comprehensive consideration of the probable damage from the time of decision-making and the degree of the models adequacy in the process of finding the optimal solution;

- consideration of features of the subject area of the object, determining the system of constraints in (1);

- use of specialized software and its adaptation to the subject area of the object of study;
- need to correct and introduce additional information in the process of finding a solution.

To account for time constraints in the synthesis process of an adequate classifier model, a formal transformation

$$F : X \rightarrow Y, X \subset \mathfrak{R}^m, Y \subset \mathfrak{R}^k, \quad (3)$$

must be performed at the additional condition that

$$R(M, O) \geq \delta \geq 0, \Delta t \leq \Delta T_0, \quad (4)$$

where X is these of samples of object description attributes;

Y is multiple states of an object;

$$X^m = \{x_1, x_2, \dots, x_m\} \subset X -$$

is a final array of training samples;

F is a functional transformation of the space of observations (features) into the space of states (decisions);

ΔT_0 is scheduled (maximum permissible) decision time;

k and m are the dimension of the states (the volume of the alphabet of classes) and the dimension of the factors (the volume of the dictionary of attributes), accordingly;

$R(M, O)$ is the distance between an object and its model in a certain metric space with a given metric $r(a, b)$,

δ is the permissible inadequacy limit in a given metric space.

Building of a real-time classifier

The basis of building an RT classifier is the technology of solving the problem of building adequate models of basic processes for a limited time.

In the neural network format, the degree of models adequacy was evaluated on the basis of the analysis of their learning errors, and the efficiency of their construction was evaluated by the training time.

The analysis of the capabilities of the neuro-emulators package of the Stat Soft environment in the format of the Statistika Neural Network module [8] revealed the potential possibilities for accelerating the preparation of input data, the choice of architectures and training methods, and verification of the decision made. In total, at application of a certain technology [6,7], the following tasks are solved:

1. Operational data import, which allows speeding up the interactive formation of a training set in a given data presentation format.

2. The transition from an interactive, empirical choice of neural network architecture to an intelligent and automatic one, based on the recognition of the most accurate and reliable models and forecasts.

3. The use of the ensemble of models as a collective expert in order to identify the best of several models with different teaching methods, characteristics

and parameters, which allow us to vary the technological modes in a wide range.

4. Construction and application of fast learning algorithms with a modification of the synaptic space in cycles of epochs with a pilot tracking of current errors, to automatically search for a compromise between the reliability of the decision made and the speed of its adoption.

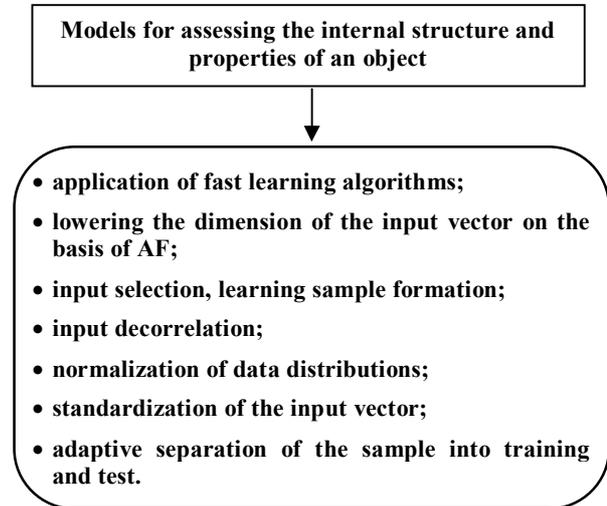


Fig. 1. The structure of accelerating processes in the object classifier

5. Creation of independent applications using the main program code, previously trained for typical situations of the complex on an array of precedents in a specific subject area, requiring only finishing training under the selected constraints. It also reduces the total time to build and adapt the model when classifying:

With this classifier modeling structure, resolve the operational response problem while decision making is reduced to the implementation of these functions by creating algorithms and programs for displaying an array of input data on the state of an object, taking into account the scheduled time.

To simulate an RT classifier, it is advisable to investigate the capabilities of the Stat Soft data technical analysis package with the STATISTICA Neural Networks neural network module [8]. Then the synthesis of models of basic processes is realized in the space of procedures that accelerate the adaptation of models within the boundaries of the chosen disciplining conditions.

Fast learning of classifier models and descent to global extremum

The network input receives many pairs of training vectors $\{x, d\}$, where $\{x\}$ is an input vector, and $\{d\}$ is a true output feature vector of the object of study, $\{y\}$ is reaction set of the neural network to the input $\{x\}$. The difference between $\{y\}$ and $\{d\}$ ($E = \|y - d\|$) is the essence of the training error.

With the mean square form of the error measure we get:

$$E = \frac{1}{SM} \sum_{i=1}^S \sum_{j=1}^M (y_j^i - d_j^i)^2, \quad (5)$$

where S is a number of training pairs, M is an output vector dimension.

The task of a neural network learning is reduced to the search for values of weights $w_i, j(k)$, to learning error E less than some value $\varepsilon (E < \varepsilon)$ when fulfilling the disciplining conditions in (1).

Simplified learning algorithms [7], for which high convergence rate, as a key quality criterion, is provided with low gradient calculation error requirements, allow realizing network training in real time.

The RPROP (resilient backpropagation) [7] algorithm solves this problem by calculating gradient signs. The algorithm does not depend on the accuracy of the calculation of the values of the derivatives, but analyzes only the ratio of signs of increments according to the rule:

$$\Delta_l^{(i)} = \begin{cases} \eta^+ \Delta_l^{(i-1)}, & \text{if } \frac{\partial E(w)^{(i-1)}}{\partial w_l} \cdot \frac{\partial E(w)^{(i)}}{\partial w_l} > 0 \\ \eta^- \Delta_l^{(i-1)}, & \text{if } \frac{\partial E(w)^{(i-1)}}{\partial w_l} \cdot \frac{\partial E(w)^{(i)}}{\partial w_l} < 0 \\ \Delta_l^{(i-1)}, & \text{if } \frac{\partial E(w)^{(i-1)}}{\partial w_l} \cdot \frac{\partial E(w)^{(i)}}{\partial w_l} = 0 \end{cases}, \quad (6)$$

where $0 < \eta^- < 1 < \eta^+$ and is determined empirically.

The increment value is adjusted by a fixed value. η^+ when the algorithm converges to a minimum and the derivative does not change sign. This speeds up the process on flat areas and slows down the search, in the case of missing a local minimum.

Then we determine the magnitude of changes in weights in accordance with the direction of decreasing gradient.

$$\Delta w_l^{(i)} = \begin{cases} \Delta_l^{(i)} \cdot \text{sgn} \left[\frac{\partial E(w)^{(i)}}{\partial w_l} \right], \\ \text{if } \frac{\partial E(w)^{(i-1)}}{\partial w_l} \cdot \frac{\partial E(w)^{(i)}}{\partial w_l} \geq 0 \\ -\Delta_l^{(i)}, & \text{if } \frac{\partial E(w)^{(i-1)}}{\partial w_l} \cdot \frac{\partial E(w)^{(i)}}{\partial w_l} < 0 \end{cases}, \quad (7)$$

where $\text{sgn}[*]$ is a function sign. The change in the sign of the derivative error in the next step indicates the function minimum. This result requires a return to the previous weight value $w_l^{(i-1)}$. The gain in time is obvious. The algorithm is based on determining only the sign of the product of the derivatives of functions in the

current and previous step. Modification of the synaptic space in this way requires a significantly smaller number of operations, compared to the classical method of error back propagation [6].

To find corrections to the weights of the elements, it is necessary to carry out the following calculations [7]:

Step 1.

If the measured value is

$$\frac{\partial E}{\partial w_{ij}}(t-1) \cdot \frac{\partial E}{\partial w_{ij}}(t) > 0,$$

the corrections are calculated:

$$\begin{aligned} \Delta_{ij}(t) &= \min(\Delta_{ij} \cdot \eta^+, \Delta_{max}), \\ \Delta w_{ij}(t) &= -\Delta_{ij}(t) \cdot \text{sign} \left[\frac{\partial E}{\partial w_{ij}}(t) \right], \\ \Delta w_{ij}(t+1) &= w_{ij}(t) + \Delta w_{ij}(t). \end{aligned} \quad (8)$$

Step 2.

If the measured value is

$$\left(\frac{\partial E}{\partial w_{ij}}(t-1) \cdot \frac{\partial E}{\partial w_{ij}}(t) < 0 \right),$$

the corrections are calculated:

$$\begin{aligned} \Delta_{ij}(t) &= \max(\Delta_{ij} \cdot \eta^-, \Delta_{min}), \\ \Delta w_{ij}(t+1) &= w_{ij}(t) - \Delta w_{ij}(t-1), \frac{\partial E}{\partial w_{ij}}(t) = 0. \end{aligned} \quad (9)$$

Step 3.

If the measured value is

$$\left(\frac{\partial E}{\partial w_{ij}}(t-1) \cdot \frac{\partial E}{\partial w_{ij}}(t) = 0 \right),$$

the corrections are calculated:

$$\begin{aligned} \Delta w_{ij}(t) &= -\Delta_{ij}(t) \cdot \text{sign} \left[\frac{\partial E}{\partial w_{ij}}(t) \right], \\ \Delta w_{ij}(t+1) &= w_{ij}(t) + \Delta w_{ij}(t). \end{aligned} \quad (10)$$

Initial increment values $\Delta_l(0)$ are randomly selected from the range (0,1).

Options Δ_{min} and Δ_{max} are selected empirically based on multiple experiments with models and their values are as follows $\Delta_{max} = 40$ and $\Delta_{min} = 10^{-4}$.

Thus, the network learning algorithm for classifier modeling is not critical to the accuracy of the calculation of partial derivatives, since it analyzes not absolute increments, but only the ratio of signs of these increments. At the same time, the volume of computational operations is reduced by several times, which reduces the total time of model adaptation.

For various simulation conditions on test samples of examples, an ensemble of productive neural networks was obtained, which qualitatively confirm the efficiency of the proposed technology of classifier synthesis in real time. Some difficulties arise in the formation of a representative sample of precedents, but this does not violate the logic and content of the implemented classifier synthesis algorithms.

Therefore, the proposed technology can be useful in upgrading the introspection complexes with a certain refinement of the source database.

Conclusions

1. Neural network support of introscopy technology is technologically and practically feasible. To automate the procedure for identifying the objects of analysis in stationary and mobile complexes of

screening analysis in order to improve the quality of classification in real time, it is constructive to use the technology of automatic recognition machine synthesis based on artificial neural networks. This problem is solved using classical multilayer perceptrons as a direct recognition problem.

2. The synthesized models of classifiers on the basis of the input data of images based on shadow and tomographic raster sweeps showed satisfactory performance and revealed prospects for their introduction into the real introscopy process. At the same time, the main efforts should be directed to the formation of a base of a representative sample of precedents, and the synthesis of models should be carried out in the environment of standard neuro-emulators, which will make it possible to solve the task at minimal cost.

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Нейромережева підтримка інтроскопії внутрішньої структури та параметрів будівельних конструкцій

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Анотація. Інтроскопія – процес безконтактного, неруйнівного аналізу внутрішньої структури об'єкта або процесів у ньому за допомогою рентгенівського випромінювання, оптичних, акустичних, ультразвукових, сейсмічних, електромагнітних хвиль різного діапазону, принципів модуляції і кодування. В її реалізації задіяні методи отримання тінювих, томографічних, радіолокаційних та ін. зображень об'єкта дослідження, в яких міститься інформація про даний об'єкт. Аналіз зображення і прийняття рішення про структуру об'єкта або його стан здійснює експерт (оператор). Ефективність аналізу залежить від кваліфікації експерта і може істотно знижуватися за рахунок зростання числа помилок і часу аналізу. У реальних умовах класифікація стану об'єкта дослідження при значній кількості ознак, з їх нестабільним або малоінформативним ступенем отримання знань представляється нетривіальним завданням. На сьогоднішній день розроблені і впроваджені в практику технології розпізнавання зображень на основі штучного інтелекту, що дозволяють синтезувати нейромережеві класифікатори в системах технічного зору, інваріантних до фізичних особливостей ознакових просторів досліджуваних образів об'єктів. Для технології інтроскопії підготовлена нейромережева інформаційно-аналітична, програмна та інструментальна основа для вирішення завдання автоматизації візуалізації зображень і їх ідентифікації в просторі тінювих, томографічних, багаторакурсних інформативних ознак із застосуванням статистичних вирішальних правил. Розроблена технологія представлена у вигляді ансамблю нейромережевих моделей класифікаторів, реалізованих самостійними програмними додатками в основному код існуючого пакету технічного аналізу, наприклад, нейроемюлятора середовища StatSoft. Синтез моделей класифікаторів за вхідними даними образів на основі тінювих і томографічних растрових розгортки в стандартному пакеті нейроемюлятора дозволяє вирішувати задачу при мінімальних витратах і необхідних показниках якості. Проведені дослідження ознакових просторів процесу інтроскопії, можливостей коректного застосування статистичних вирішальних правил, алгоритмів примусового навчання синтезованих нейромережних моделей в базисі існуючих пакетів технічних даних дозволяють підвищити продуктивність технічних засобів інтроскопії шляхом автоматизації процесу аналізу, зниження впливу суб'єктивних рішень, скорочення часу реакції.

Ключові слова: аналітичний комплекс, інтроскопія, нейронна мережа, метод зворотного поширення помилки, класифікатор реального часу.